Estimation of Large Truck Volume Using Single Loop Detector Data

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ABSTRACT

This paper presents a methodology to estimate the volume of large trucks by using single loop outputs. An Unscented Kalman Filtering (UKF) algorithm is used to generate speed estimation based on single loop data, and the mean effective vehicle length of each time interval is thus obtained with the loop outputs and speed data provided. We investigated the bimodal vehicle length distribution and further separated it into short and long vehicle distributions. Based on the estimated mean effective vehicle lengths and vehicle length distributions, an algorithm is proposed to estimate large truck volume. Data collected from Texas Transportation Institute's vehicle detection test beds are used for this study. The results show that the proposed method produces good performances in large truck volume estimation under various traffic conditions.

Key Words: Trucks; Volume Estimation; Single Loop Detectors

INTRODUCTION

Truck traffic has been increasing steadily on America's highways due to the growing economy and increased international trade. Trucks have different characteristics from passenger cars and thus are a key consideration in many stages of a highway project. Trucks are critical to transportation planning, pavement design, geometric design, and traffic operations. With the rapid growth of truck volumes on highways, safety with respect to trucks has also received more and more attention.

Vehicle classification information can be obtained from vehicle detection equipment with a specific classification mechanism. Visual, axle, and presence sensors are three common types of detectors used for truck identification. The presence sensors, such as loop detectors, are the most widely used detectors in the U.S. due to their cost-effectiveness. Dual-loop (double loop) detectors can measure vehicle length information and act as a crude vehicle classifier (*1*). For single loop detectors, however, the vehicle length and classification information is not available in the output. Since single loops are a very common type of detector in the field that provide online traffic data, an effective estimation method for vehicle length and truck traffic based on single loop output would be very useful for real-time traffic management and control

Research in the estimation of large truck volume from single loop outputs has attracted more and more attention in recent years. A study in the state of Washington (*2*) proposed a pattern discrimination method to estimate large truck volume using single loop data. One assumption used in that study is that vehicle speeds in each five-minute time period are consistent and speed variance can be ignored. The developed method is hence suitable for stable traffic conditions without large speed variations. Another study in California (*3*) used lane-to-lane speed correlation to estimate large truck volume using data from single loop detectors. They assumed that the percentage of large trucks in the leftmost lane can be ignored, and vehicle speeds over different lanes tend to be synchronized. However, due to wide ranges of traffic and geometric conditions, variations of speeds and truck lane distribution can be very significant. The assumptions made in the prior studies may not be valid for some types or locations of highways or for some traffic conditions. This drawback limits the application scope and may affect the effectiveness of the approach. Most recently, an Artificial Neural Network (ANN) was proposed for vehicle classification using single loop outputs (*4*). Four length-based vehicle classification categories were used in this study. The results showed that this method performs well for two categories with the shortest and the largest vehicle lengths. The performance of an ANN is directly related to the training dataset that is used, and overprediction based on limited training data is often associated with ANNs.

This paper provides a new methodology to estimate the volume of large trucks from single loop detector outputs. In this study, a Large Truck (LT) or a long vehicle is defined as a truck with a length greater than or equal to 12.19 m (40 feet) as in the studies of Wang and Nihan (*2*) and Kwon *et al.* (*3*). An accurate single loop speed estimation algorithm using an Unscented Kalman Filter (UKF) is employed to generate speed data, and the Mean Effective Vehicle Length (MEVL), which is equal to the sum of average vehicle length and single loop detector length, can then be calculated at each time interval. The paper then investigates the overall vehicle length distribution as well as short and long vehicle length distributions. An algorithm is then proposed to estimate LT volumes based on the MEVL and vehicle length distributions. Finally, estimation results are presented and evaluated with data collected from two vehicle detection test beds.

DATA FOR THE STUDY

The data we used are collected from two freeway locations, State Highway 6 (SH6) near the FM 60 (University Drive) Bridge in College Station, Texas, and Interstate Highway 35 (IH-35) near the 47th street exit in Austin, Texas. Texas Transportation Institute (TTI) has two test beds at those locations. SH6 has two lanes in each direction while IH-35 has four at the test bed location. Data are collected using Peek ADR 6000 detectors, each of which includes two inductive loops embedded in the pavement. This relatively new ADR 6000 detector adopts the inductive loop technology and generates accurate outputs of vehicle presence time, speed, count, vehicle length, and vehicle classification (*5*). Count and occupancy data, which are typical outputs of single loop detectors, can be extracted from vehicle presence times (the duration a vehicle passing a single loop) with a certain time interval for speed and vehicle length estimation purposes. Vehicle classification, vehicle length, and speed data are also available for every time interval from the detector outputs and are used to compare with estimation results to assess the performances of the estimation algorithms.

Traffic volume on SH6 is moderate, with daily volume around 13,000 vehicles for the right lane, and 10,000 vehicles for the left lane. Most vehicles were traveling at high speeds at this location. Traffic volume is high on IH-35, with an average daily volume over 27,000 vehicles for the rightmost lane, and about 15,000 vehicles for the leftmost lane. Congestion repeatedly occurred during morning and afternoon peak hours. During those congested periods, vehicles traveled at very low speeds and many experienced stop and go situations. The rightmost lanes of both locations are selected for this study because they experienced the worst traffic conditions and contained the highest LT percentages. Data were collected for one weekday from each test bed (January 27, 2004 on northbound SH6 and October 27, 2004 on southbound IH-35) and compiled into 30-second time intervals, which is a common type of time interval used by single loop detectors.

Large Truck Classifications

As has been mentioned before, whether a vehicle is a LT or not is determined by its length in this paper. Thus, in the LT volume estimation using single loop outputs, vehicles are simply classified into two types: short vehicles (less than 12.19 m) and large trucks (greater than or equal to 12.19 m). This way of classification is different from the "*Vehicle Classification Scheme F*" (*6*), which classifies vehicles into 15 types with 13 types explicitly defined based on the number of axles, axle spacing, and other features of vehicles. In the "*Scheme F*" that are used by most state DOTs, classes 5 to 13 are classified as trucks. Trucks of class 5 (single-unit trucks) have two axles and those of classes 6 to 13 have three axles or more.

With data collected from Peek systems, we are able to discover the difference between LTs and trucks. We conducted a comparison of LTs (based on length) and trucks with three axles and up, using two-day data collected from the test beds. Results of the comparison are shown in Table 1. It is found that the percentages of LTs based on vehicle length are only slightly less than those of trucks with three or more axles based on the "*Scheme F*". Therefore, based on our data, the LT classification based on vehicle length in this study is reasonable and the LT results can be used to represent all trucks excluding single unit trucks from the "Scheme F" classification method.

METHODOLOGY

In order to determine LT volume from single loop detector data, the most critical parameter to be determined in this study is the MEVL in a time interval. Since both vehicle lengths and speeds are unknown, one way to obtain the MEVL is to employ some algorithms to first estimate the average speed at each time interval.

Speed Estimation Using the UKF

For time interval i with duration T, assume N_i vehicles pass over a loop detector, vehicle j has speed s_{ij}, and the effective vehicle length (EVL), defined as the vehicle length plus single loop length, is L_{ij}. The occupancy is then defined by

$$O_i = \frac{1}{T}\sum_{j=1}^{N_i}\frac{L_{ij}}{s_{ij}} + \varepsilon_i \quad (1)$$

where ε_i is a zero-mean noise of occupancy. Dailey (*7*) has statistically transformed this equation to an aggregated level. Assume perfect measurement ($\varepsilon_i = 0$) for a loop detector, Equation 1 is transformed to

$$\frac{N_i}{O_i} = \frac{T \times \bar{s}_i}{\bar{L}_i}[\frac{1}{\sigma_s^2 / \bar{s}_i^2 + 1}] \quad (2)$$

where $\bar{s}_i$ is the mean speed, σ_s^2 is the speed variance and $\bar{L}_i$ is the MEVL at *ith* time interval.

A number of research efforts have been conducted to estimate speeds using single loop outputs (*8*; *9*; *10*). However, most previous studies of speed estimation cannot produce very accurate estimates under various traffic conditions due to various simplifications and linear assumptions. As described in Equation 2, the problem of speed estimation is a nonlinear system. An Extended Kalman Filtering (EKF) technique was proposed to solve this problem through linearization (*7*). However, this filtering technique has its weaknesses in dealing with nonlinear systems (*11*, *12*). Particularly, its inability to make good predictions of the system state, observations, and associated covariance matrices when the system and/or observation models are nonlinear affects prediction accuracy..

Recently, Ye *et al.* (*13*) proposed a UKF method for speed estimation. This method is able to generate highly accurate speed estimates under both normal and congested traffic conditions. The speed estimation is not the main focus of this paper and it can be also independent from the LT estimation methodology proposed in this paper. However, to make this paper self-sufficient, the UKF is briefly discussed here.

The fundamental part of the UKF is the Unscented Transformation (UT) (*12*). It uses a deterministic algorithm to sample a set of weighted sigma points, which are applied to parameterize the means and covariances of probability distributions.

For a *d*-dimensional random variable x with mean $\bar{x}$ and covariance P_{xx}, $(2d+1)$ weighted sigma points are drawn to approximate the random variable. The $(2d+1)$ sigma points $\{\chi_0,...,\chi_{2d}\}$ are determined by

$$\begin{aligned}
&\chi_0 = \bar{x}, && \mathrm{W}_0 = \kappa/(\mathrm{d}+\kappa) \\
&\chi_i = \bar{x} + (\sqrt{(d+\kappa)P_{xx}})_i\ , && \mathrm{W}_i = 1/[2(d+\kappa)],\ i = 1,...,d \\
&\chi_{i+d} = \bar{x} - (\sqrt{(d+\kappa)P_{xx}})_i\ , && \mathrm{W}_{i+\mathrm{d}} = 1/[2(d+\kappa)],\ i = 1,...,d
\end{aligned}$$

where $\kappa \in \Re$ provides an extra degree of freedom to fine-tune the higher order moments of the approximation, P_{xx} is the covariance of random variable *x*, $(\sqrt{(d+\kappa)P_{xx}})_i$ is the *ith* row or column of the matrix root of $(d+\kappa)P_{xx}$, and W_i is the weight associated with the *ith* sigma point.

After sigma points are selected, the UKF will undergo two steps at each time interval: the time update step and the measurement update step. The time update step predicts the state and covariance, and the measurement step corrects the state and covariance with consideration of the most recent observation. The operation process of the UKF is shown in Figure 1. The calculated sigma points are used in both time update and measurement update steps to approximated mean, covariance and cross-variance of both state variable $\bar{s}_i$ and measurement variable N_i/O_i. For more details about the UKF algorithm, refer to (*13*).

Estimation of the MEVL

As the mean speed $\bar{s}_i$ is estimated using the UKF at each time interval, the MEVL for the time interval ($\bar{L}_i$)is obtained by rearranging Equation 2:

$$\bar{L}_i = \frac{O_i \times T \times \bar{s}_i}{N_i}[\frac{1}{\sigma_s^2 / \bar{s}_i^2 + 1}] \tag{3}$$

O_i and N_i are occupancy and count for the *i* th time interval and are directly from the single loop output. Once the MEVL is determined, it will be used for further LT volume estimation.

Estimation of LT Volume

Vehicle Length Distribution

In the study by Wang and Nihan (*2*), a large sample of vehicle lengths was collected from dual-loop detectors and it was found that there were two peaks in the distribution of vehicle length. After separating vehicle lengths less than 12.19 m (40ft) from the lengths greater than 12.19 m, two vehicle length distributions were obtained and each fit a normal distribution very well.

In this paper, a sample of vehicle lengths from IH-35 was chosen for the study of vehicle length distribution. The Kernel density of vehicle lengths is shown in the part “a)” of Figure 2. The density plot displays a bimodal distribution of vehicle lengths. Small vehicle lengths are highly concentrated around 5 m and long vehicle lengths are distributed around 20 m. In order to investigate the distributions of small and long vehicles, the sample was separated into two groups, using 12.19 m as the separation point. To examine if both samples fit normal distributions, normal probability plots were utilized. Parts “b)” and “c)” of Figure 2 show the Q-Q plots of short and long vehicle lengths. A Q-Q plot can be used to determine graphically if a dataset comes from a normal distribution. Obviously, the distribution of short vehicle lengths is highly right skewed and the distribution of long vehicle lengths is left skewed. The distributions of both short and long vehicle lengths are not normally distributed.

The methodology of LT volume estimation in this paper does not hinge upon the normal distribution assumptions. No matter what kind of distribution vehicle lengths fit for, we assume that the mean values of short and long vehicle lengths are u_1 and u_2. It is also assumed that the short vehicle length distribution X and the long vehicle length distribution Y are independent. Then the average vehicle length at each time interval will be subjected to a distribution with the expectation $u = p_1 * u_1 + p_2 * u_2$, where p_1 and p_2 denote the proportions of short and long vehicles. At *ith* time interval, assume that N vehicle are detected, and suppose that n_1 vehicles are short vehicles and n_2 vehicles are LTs. Then, $X_1, X_2, ..., X_{n_1}$ form a random sample from the distribution X, and $Y_1, Y_2, ..., Y_{n_2}$ form the other random sample from the distribution Y. To compute the average vehicle length (τ_i), we simply take the expectation

$$\begin{aligned} \tau_i &= E\left[\frac{X_1 + X_2 + \cdots X_{n_1} + Y_1 + Y_2 + \cdots + Y_{n_2}}{N}\right] \\ &= E\left[\frac{n_1 \times u_1 + n_2 \times u_2}{N}\right] \\ &= \frac{n_1}{N} \times u_1 + \frac{n_2}{N} \times u_2 \end{aligned} \qquad (4)$$

where $n_1+n_2=N$, and the average vehicle length (τ_i) equals to the MEVL minus single loop length.

Two samples of historical vehicle length data from IH-35 and SH6 are gathered to generate vehicle length distributions of both short vehicles and LTs. Mean length (u_1) of short vehicles is around 4.88 m at SH6 and 4.72 m at IH-35; mean LT length (u_2) is about 18.96 m at SH6 and 19.39 m at IH-35. IH 35 is an urban freeway while SH6 is a rural area. The truck percentages are significantly different as shown in Table 1. However, u_1 and u_2 are about the same. Further investigation showed that at both locations, u_1 and u_2 for different time periods pretty much stay the same even though truck volumes and percentage may vary significantly between time periods. Therefore, u_1 and u_2 are treated as known parameters in our method and can be determined based on samples from historical vehicle length data from a similar highway in the area.

Estimation of LT Volume

Given the MEVL value estimated in the previous section and the number of vehicles at a certain time interval, we can calculate the number of LTs during this time period by rearranging Equation 4:

$$n_2 = \frac{N(\tau - u_1)}{(u_2 - u_1)} \tag{5}$$

where u_1 and u_2 are mean short vehicle and LT lengths corresponding to a specific highway or location. Note that n_2 is rounded to the nearest integer.

RESULTS AND DISCUSSIONS

One set of weekday data from each TTI's test bed, as described in the second section, is processed and analyzed. The UKF algorithm is firstly used to generate speed information. Then the average vehicle length at each time interval is calculated through Equation 3. Comparisons between estimated and observed speed data, of 30 second time intervals in a day are shown in parts "a)" and "b)" of Figures 3 and 4. The results demonstrate that the UKF does well in speed estimation under both normal and congested conditions. The Root Mean Square Error (RMSE) is used for the evaluation of speed estimation. The RMSE is square root of Mean Square Error (MSE), which can capture both the variance of errors and the bias of estimates. The RMSE values are shown in parts "b)" of Figures 3 and 4. The estimated MEVL and vehicle length estimation errors for all 30 seconds intervals are shown in parts "c)" and "d)" of Figures 3 and 4. It should be noted that the estimation errors of the MEVL shown in the part "d)"s of Figures 3 and 4 have some larger values and variations during nighttime and during daytime when traffic congestion exists, indicating potential estimation accuracy issues for both time periods. The observed average vehicle lengths between midnight and 6 a.m. are generally longer than 12.19 m from the part "c)"s of Figures 3 and 4, a result of very high percentage of LTs in early morning hours when few passenger cars are on the road.

With speed and MEVL estimated, the LT volume at each time interval is obtained. For better illustration, LT volume data are aggregated into 1-hour intervals. Figure 5 shows both observed and estimated LT volumes. The estimation curves capture the observation curves very well during most hours of the day. A summary of hourly-based estimation results of LT volume for the entire day is described in Table 2. In this table, two Measurements of Effectiveness (MOEs) are used: the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). They are defined as

$$\begin{aligned} MAE &= \frac{1}{24}\sum_{i=1}^{24}\left|\hat{n}_{est.}^{(i)} - n_{obs.}^{(i)}\right| \\ MAPE &= \frac{1}{24}\sum_{i=1}^{24}\left|\frac{\hat{n}_{est.}^{(i)} - n_{obs.}^{(i)}}{n_{obs.}^{(i)}}\right| \end{aligned} \tag{6}$$

where $\hat{n}_{est.}^{(i)}$ is the estimated LT volume during *ith* hour and $n_{obs.}^{(i)}$ is the observed LT volume. The overall estimated LT percentages are very close (within 0.5%) to observed percentages with slight underestimations. By comparing the estimated LT percentages with truck percentages that are computed based on vehicle classifications and shown in Table 1, the estimation errors are less than 1% for both data sets.

To further explore the factors affecting estimation results, the effects of LT percentage and traffic volume level are investigated using the SH6 data. Firstly, a study of estimation errors under different traffic volume levels is conducted. Part “a)” of Figure 6 illustrates hourly traffic volumes throughout the experiment while part “c)” of this figure shows hourly Absolute Percentage Errors (APEs). Based on parts “a)” and “c)” of this figure, it is observed that APE values during nighttime when traffic volume is relatively low are generally not much smaller than those during daytime when traffic volume is relatively high, indicating that overall traffic volume does not seem to affect LT estimation accuracy. Secondly, hourly-based LT percentages are also calculated from the observed dataset and shown in the part “b)” of Figure 6. The LT percentages are very high between midnight and 6 a.m., and the maximum percentage is close to 40%. Nevertheless, the relative larger estimation errors in the part “c)” are not generated during those high LT percentage hours. Thus, the LT percentage itself does not show significant effects on the LT volume estimation either according to our experiment. From Figure 6(c), there are periods of time during the day when there are more fluctuations in APE. For example, at the 22:00 hour, the APE reaches 20%. However, a closer looking at Figure 5 reveals that the estimation error for the hour is only three LTs, 18 estimated versus 15 observed, and obviously acceptable. In addition, the fluctuations illustrated in Figure 6(c) are centered around the MAPE line, indicating no system error trend with respect to any particular factor. This seems to indicate that the estimation results are not significantly affected by either LT percentage or overall traffic volume.

To further investigate the performance of the algorithm under various traffic conditions, particularly under congested conditions, data of two consecutive days (November 9 and 10, 2004) from IH-35 site were analyzed. The site has regular AM and PM recurrent congestion periods. Figure 7 presents LT estimation results along with speed estimation results and Figure 8 illustrate the LT estimation error distribution. For this analysis, LTs are estimated at 15-minutes interval, an interval commonly used in real-time traffic flow prediction. It can be seen that again MAPE line centers around zero, indicating no systematic estimation errors. A closer look into the error distribution of the LT estimation at 15-minute interval in Figure 8 show that there are only 6 intervals that have error over 15 LTs per interval, or 1 LT per minute on average. About 90% of the intervals have errors smaller than 10 Lts per interval. About 80% of the intervals have errors of less than 8 LTs, or about 1 LT every 2 minutes. That's certainly good accuracy for practical applications.

From Figure 7, with the exception of early morning periods during which overall traffic is very light but LT percentage is very high, LT estimation accuracy did not seem to show any trend with respect to overall traffic volume, LT volume, or LT percentage. During the early morning periods (when LT% is at the highest), LT estimation accuracy is the best. The worst estimation accuracy occurred during the periods of congestion. A further investigation reveal that for the AM peak on the first day and both the AM peak and PM peak on the second day the speed estimation results are not as good as the rest of the periods. Coincidently, those are the same three periods that have significant LT estimation errors. This indicates that traffic congestion is a factor influencing the LT volume estimation results. Traffic congestion affects speed estimation and consequently contributes to the accuracy of LT estimation.

CONCLUSIONS

This paper firstly uses an accurate speed estimation method to estimate speed and mean effective vehicle length based on single loop detector outputs. A vehicle length sample is selected to investigate length distributions, including short and long vehicle length distributions. This paper does not assume that either short or long vehicle length distribution fit a normal distribution and proposes an algorithm for LT volume estimation based on vehicle length estimation results. Data collected from two Texas Transportation Institute's vehicle detection test beds are used for this study. The estimated large truck volumes are compared with field data. The results show that the proposed method has good performances under various traffic conditions. Finally, the factors that influence the estimation accuracies are explored. It is found that while LT percentage and traffic volume generally do not significantly affect estimation accuracy, traffic congestion is a factor affecting the results of large truck volume estimation for the congested periods mainly due to the fact that speed estimation under congested flow conditions are typically less accurate.

Real time large truck volume can be easily estimated using this proposed method and provide useful information for traffic management and control in an Intelligent Transportation System (ITS). The results can also be valuable to detailed and more reliable analyses such as level of service (LOS) analysis of a freeway segment or safety study of a location at a given demand level.

It should be pointed out that the UFK speed estimation method is used in the paper for the purpose of providing reliable speed inputs for the LT estimation methodology. Any accurate speed estimation method using single loop data can work with the LT estimation methodology proposed in this paper.

This study uses ADR sensor that provides more reliable and accurate measures of flow and occupancy than a normal single loop detector. ADR data are also used as ground truth data for validation. Actual single loop detectors have more measurement error such as missing data or erroneous readings. Because of this, further investigation and validation with actual single loop and ground truth data are needed in the future.

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TABLE 1 Comparison of Truck Classification Results Based on "Scheme F" and LTs

	Daily Traffic Volume (Veh.)	Trucks (Based on Scheme F)		LT (Based on Length)	
		Number of Trucks (Veh.)	Percentage (%)	Number of LT (Veh.)	Percentage (%)
IH-35	27670	3289	11.89	3181	11.50
SH6	13037	903	6.93	816	6.26

TABLE 2 Results of Hourly-Based Estimation of LT Volume

	Traffic Volume (veh.)	Number of LT		Total LT Error (veh.)	MAE of LT (veh.)	MAPE of LT (%)
		Real (veh.)	Estimated (veh.)			
SH6	13037	816 (6.26%)	795 (6.10%)	-21	2.54	7.57
IH-35	27670	3181 (11.50%)	3064 (11.07%)	-117	11.95	9.34

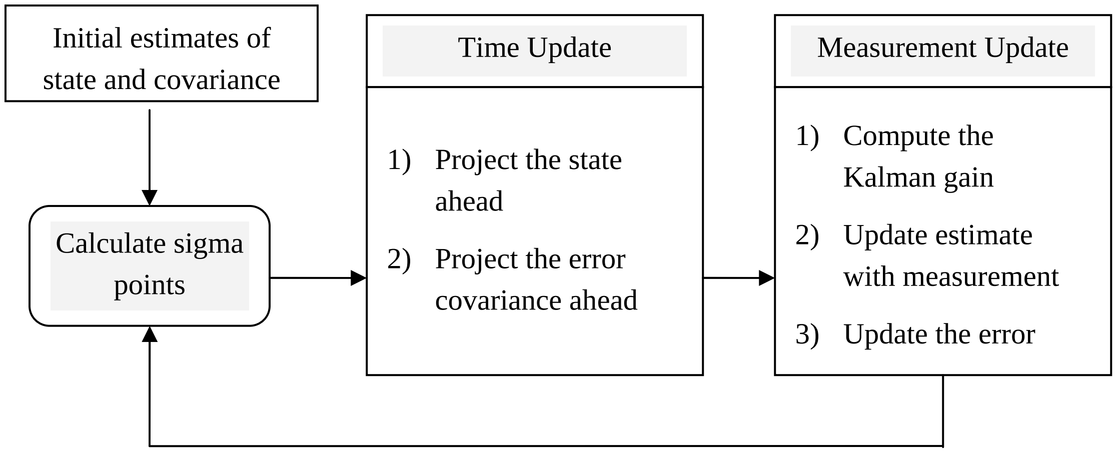

FIGURE 1 Operation process of the UKF.

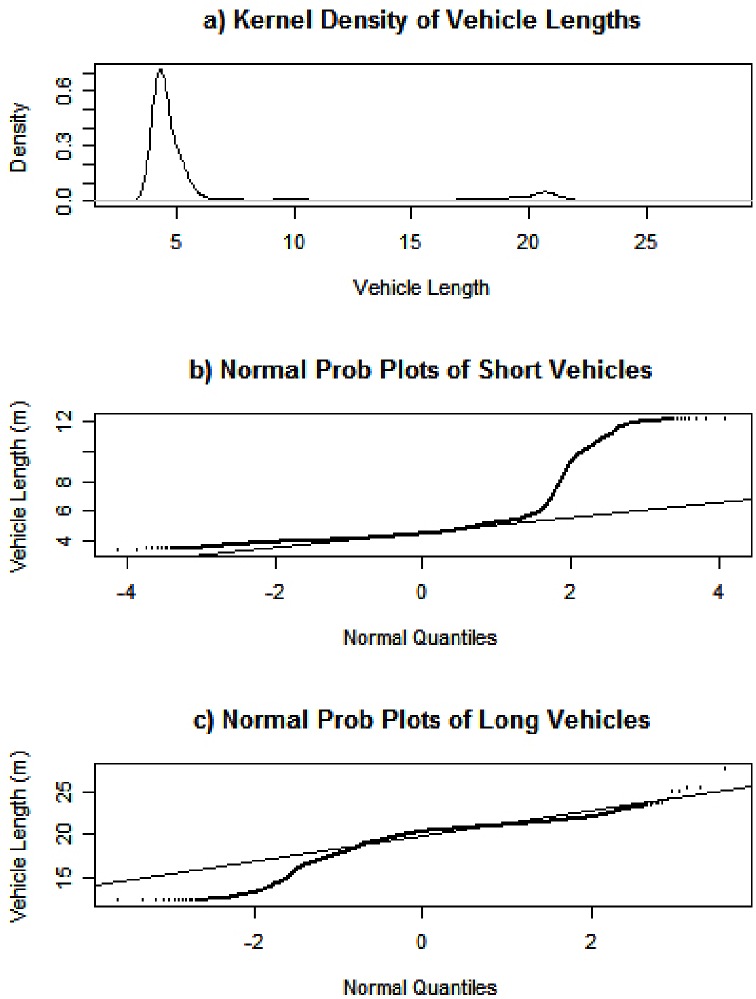

FIGURE 2 Vehicle length distributions. a) Kernel density of vehicle lengths. b) Q-Q plot of short vehicle lengths. c) Q-Q plot of long vehicle lengths.

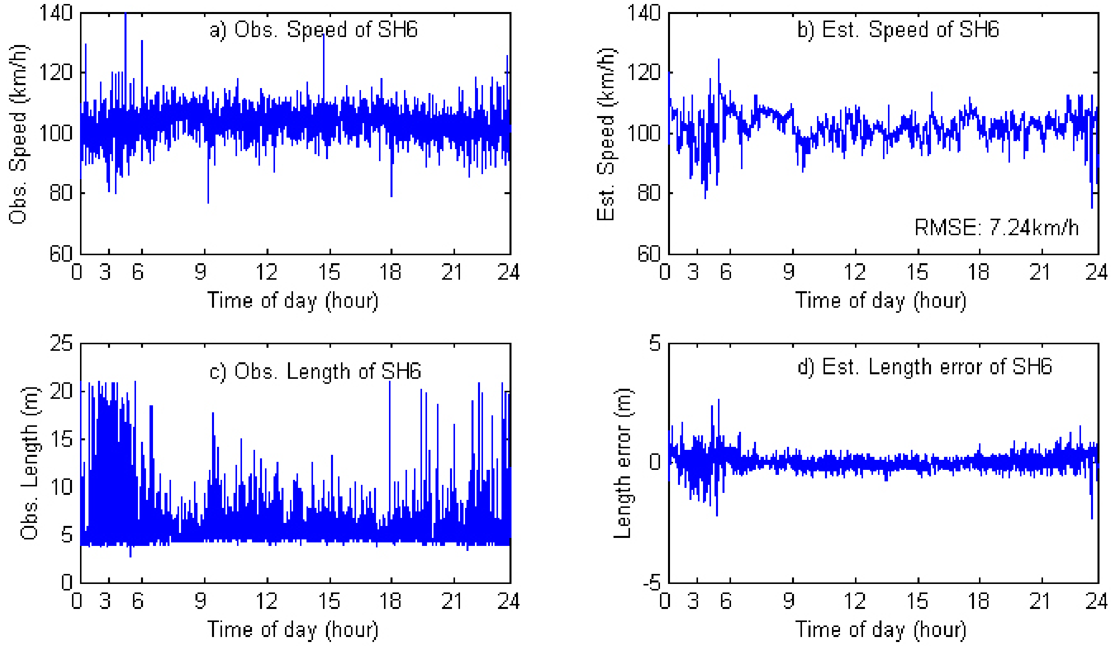

FIGURE 3 Speed and vehicle length information of SH6 (Jan. 27, 2004). a) Observed speed. b) Estimated speed using the UKF. c) Observed vehicle lengths. d) Estimation error of vehicle length.

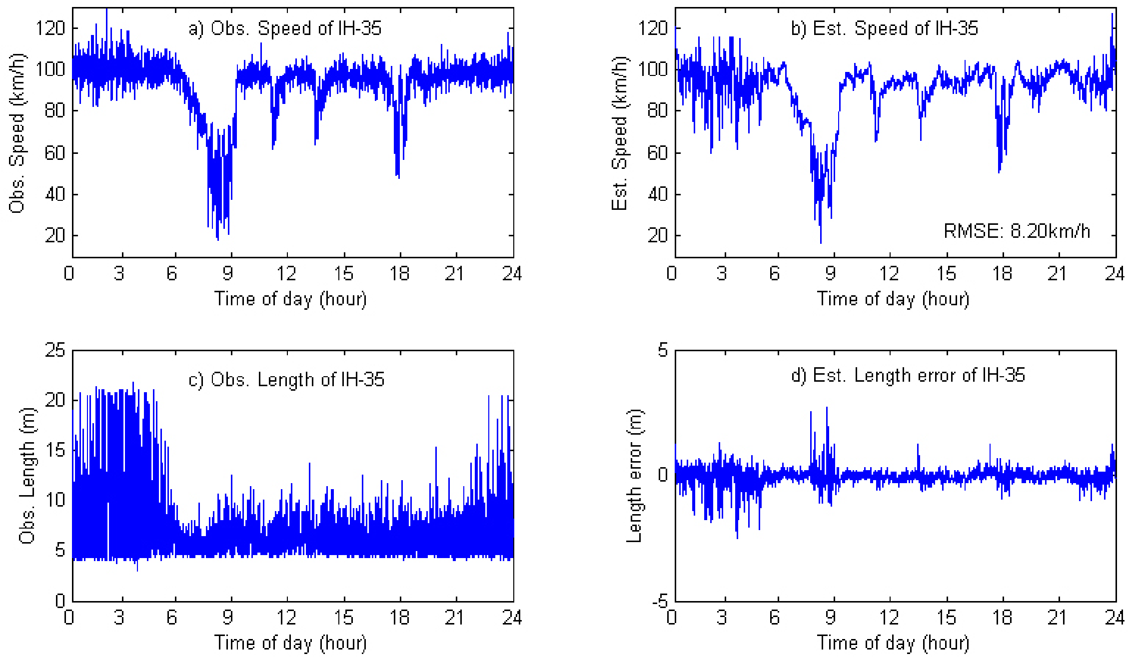

FIGURE 4 Speed and vehicle length information of IH-35 (Oct. 27, 2004).

a) Observed speed. b) Estimated speed using the UKF. c) Observed vehicle lengths.

d) Estimation error of vehicle length.

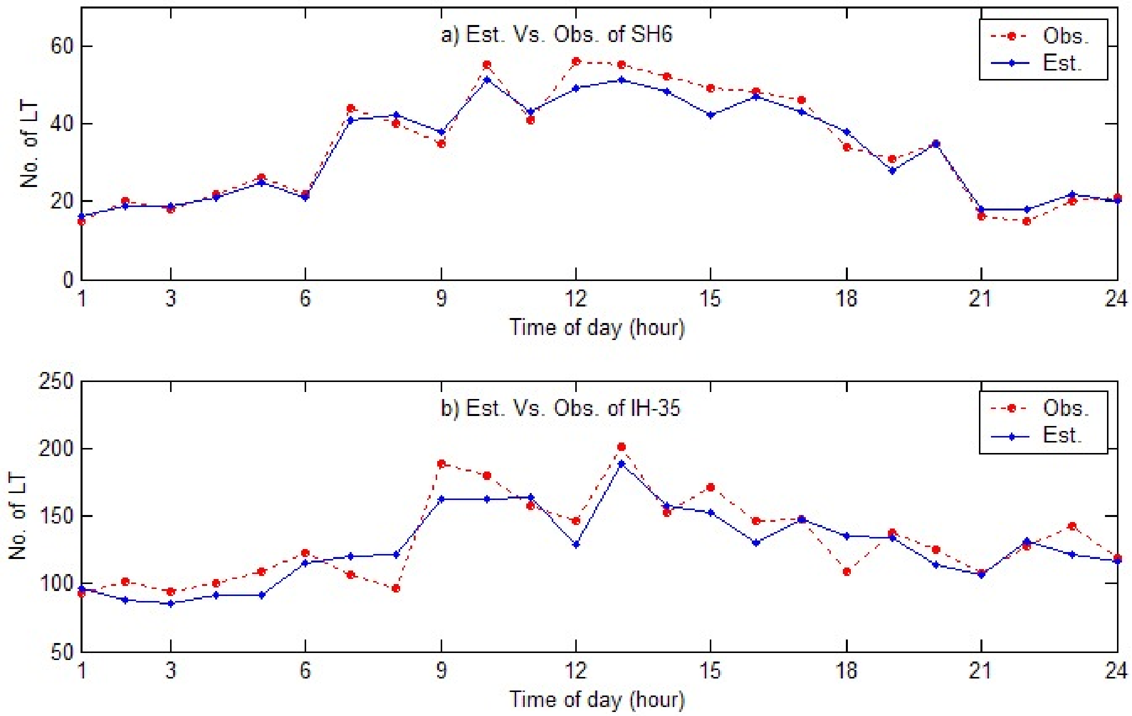

FIGURE 5 Observed and estimated LT volumes. a) Hourly-based LT volumes on SH6. b) Hourly-based LT volumes on IH-35.

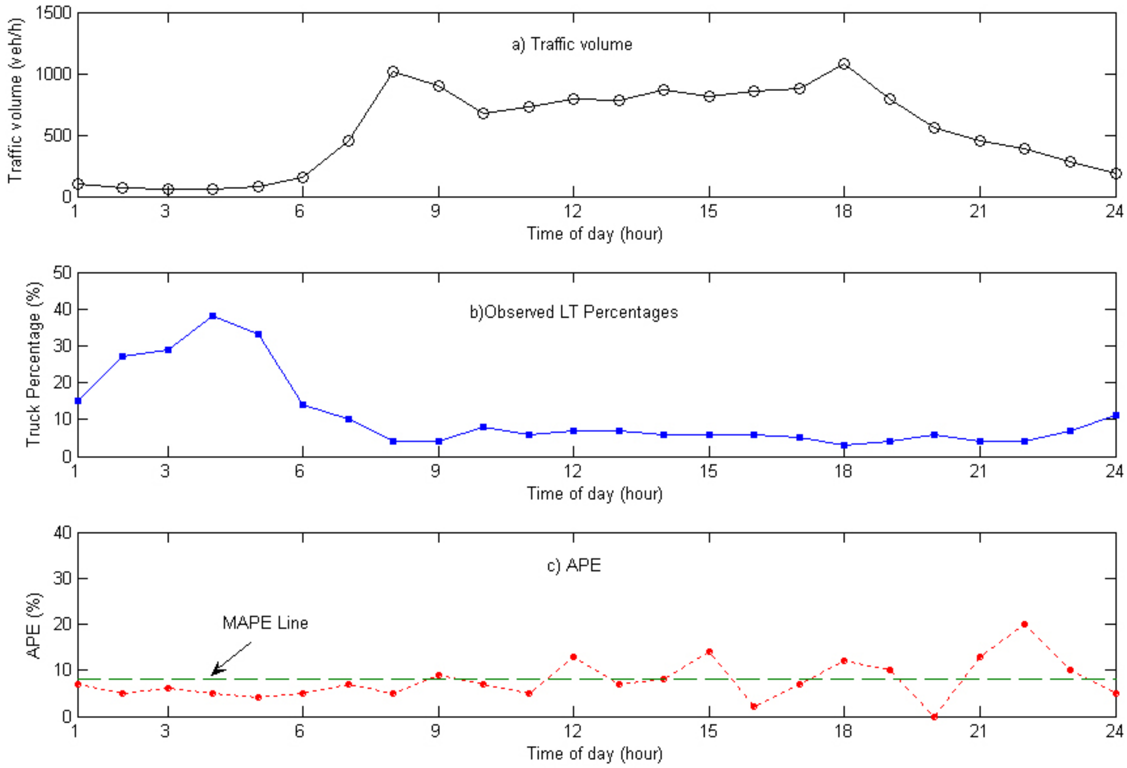

FIGURE 6 Hourly-based traffic volumes, LT percentages and estimation errors on SH6. a) Traffic volume. b) LT percentages. c) APE.

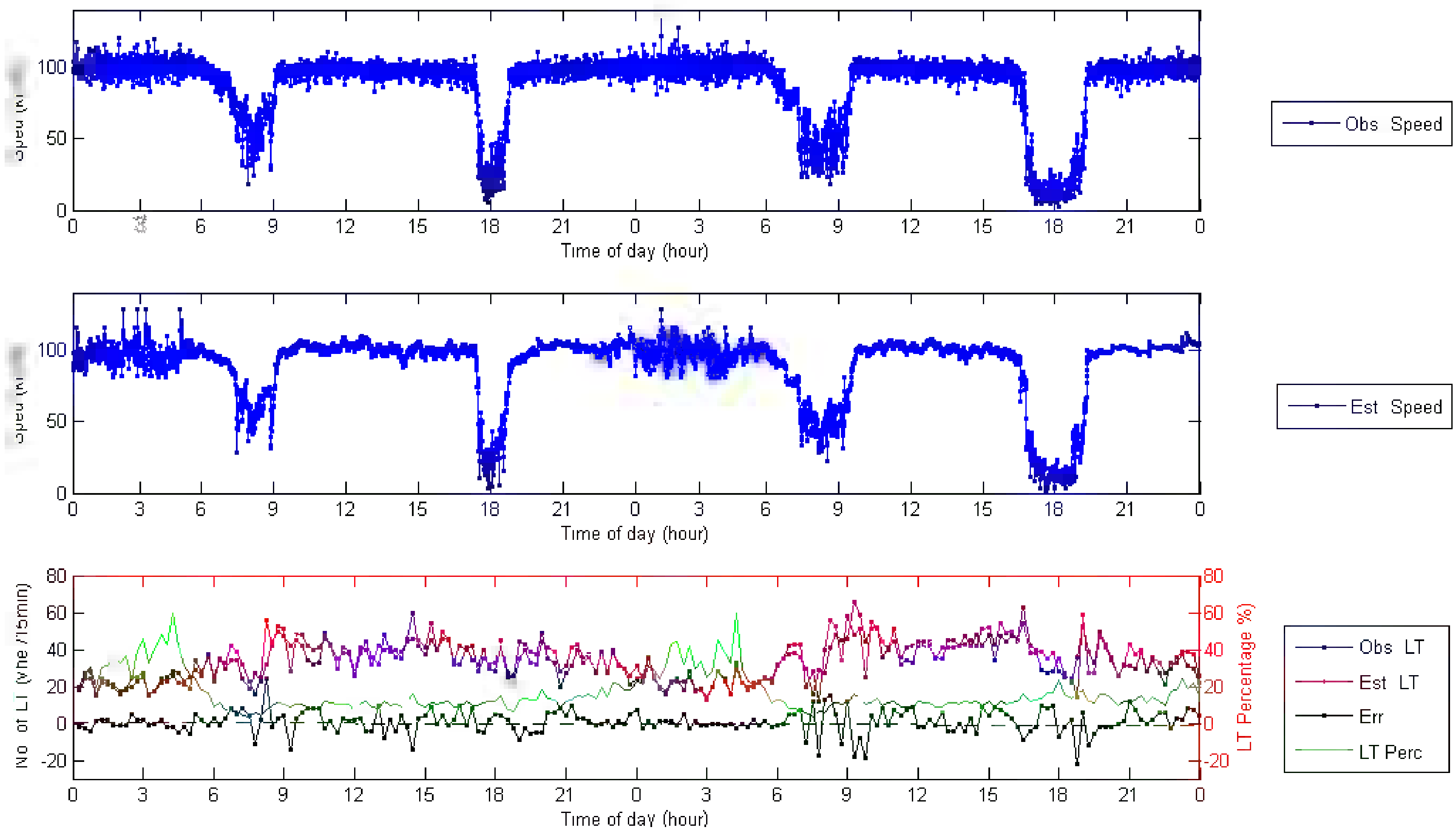

FIGURE 7 Speed and LT Volume Estimation Results for IH-35 (Nov. 9-10, 2004).

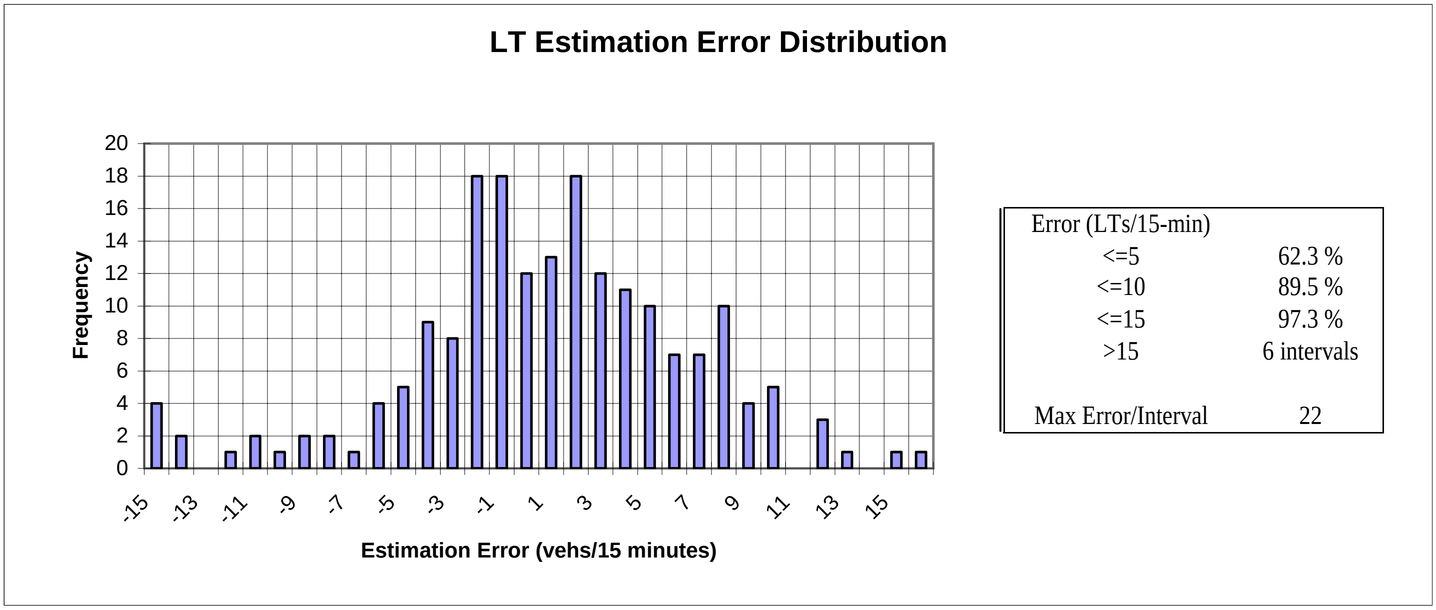

FIGURE 8 IH-35 LT Estimation Error Distribution (Nov. 9-10, 2004).